Inequality and Economic Growth: Bridging the Short-run and the Long-run

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Abstract

I analyze whether the effect of inequality on growth changes over different time-frames (short, medium and long-run). I construct a large dataset that covers the period 1950-2007 and around 100 countries depending on the specification. Using restricted system-GMM estimators I find evidence of a short-run (5-year periods) inverse-U relationship between inequality and growth. This inverse-U relationship remains in the medium-run (10-year periods). However, this association disappears in the long-run (20-year periods). Instead, for this time frame I find evidence that inequality has a negative effect on growth in poor countries, but a positive effect in rich ones. Finally, in the 37-year period (1970-2007) I find that higher inequality is associated with a lower rate of growth. Thus, while some (but not much) inequality is good for growth in the short-run and in the medium-run, the relationship changes in the long-run when it becomes dependent on the level of income, and in the very long-run inequality has a detrimental effect on growth.

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1 Introduction

Economists have longed studied the relationship between income inequality and economic growth. While the theoretical literature has developed a variety or arguments that favor either a positive or a negative relationship, by the end of the 1990's it seemed that at the empirical level the question had been resolved: Benabou (1996); Alesina and Rodrik (1994); Persson and Tabellini (1994) and Perotti (1996) showed that inequality has a negative effect on subsequent growth. By the beginning of the 2000's, however, this conclusion was challenged. Barro (2000) found that the effect of inequality on growth depends on the countries' level of income: higher inequality tends to retard growth in poor countries, but to accelerate it in rich ones. Li and Zou (1998) and Forbes (2000) found a positive short-run relationship between income inequality and growth. Moreover, Chen (2003) and Banerjee and Duflo (2003) found evidence that inequality and growth are not linearly related but instead are associated in an inverted-U pattern.[1] Thus, the question about the relationship between income inequality and economic growth remains open both at the empirical and at the theoretical level.

While most of the literature has not made an explicit distinction between the short-run and long-run effects of inequality on growth, the findings in this paper show that they might differ significantly. The basic argument is in line with the recent paper by Halter, Oechslin, and Zweimüller (2010), who argue that the positive and negative effects of inequality on growth tend to cluster over different time-frames: the positive effects tend to dominate the short-run, while the negative ones dominate the long-run. Furthermore, they present evidence that the short-run effects are captured by difference-based estimators (e.g., the Arellano and Bond estimator), while the long-run effects are captured by level-based estimators (e.g., the system GMM estimator developed by Arellano and Bover (1995) and Blundell and Bond (1998)). In contrast to Halter et al. (2010), however, I include the possibility that the effect of inequality on growth may be non-linear, as has been convincingly argued by Banerjee and Duflo. I find evidence that the short and medium-run relationship is indeed non-linear, followed by a turning point after which, in the very long-run, it becomes linear and negative. A possible explanation for these results relies on the degree of sustainability of inequality, which considers the political economy and social unrest arguments along with the accumulation incentives argument. In particular, while some inequality is required for people to have an incentive to accumulate physical and human capital, if inequality increases past a given tolerance threshold, those affected by it will demand transfers and engage in disruptive activities. From a theoretical perspective, there are two dimensions that determine this threshold: i) the magnitude of inequality, and ii) the persistence of inequality. In the literature, only the first one has been analyzed, so I discuss it first. Increases in inequality will have a negative impact on growth due to the added social unrest and distortionary transfers that

[1] Note that these findings differ from the Kuznets curve proposed by Kuznets (1955, 1963). While the Kuznets curve refers to the relationship between inequality and the *level* of income per capita, the more recent studies analyze the relationship between inequality and the *growth rate* of income per capita.

take place within the society. Combining this with the accumulation incentives argument leads to an inverse-U relationship between inequality and growth *in the short and medium-run*. Inequality persistence becomes relevant in the long-run because even a relatively low level of inequality may become intolerable when people have gone through it for some time. If that is the case, a higher level of inequality would be associated with lower growth.

In this paper I provide evidence that using a larger dataset and a restricted system GMM estimator some of these results are confirmed while others appear to emerge from limitations in the data and/or the econometric estimators used. The contribution of the paper is to analyze the effect of inequality on growth over different period lengths using the same econometric technique. This allows a direct comparison of results that so far have been analyzed only separately. I also make an attempt to find the effect of growth on inequality over the very long-run, but using a standard cross-section. In the short-run, in contrast to Forbes (2000), I find that the relationship between (lagged) inequality and growth is shaped as an inverse-U. This is consistent with Banerjee and Duflo (2003) who find that concurrent changes in inequality and growth have an inverted-U relationship over 5-year periods. This effect of inequality on growth remains when I use 10-year periods. However, it disappears in the long-run (20-year periods). Indeed, over this time span there does seem to be a reversal in the relationship (the coefficient on inequality becomes negative) conditioned on the level of income per capita. In particular, I find evidence consistent with Barro (2000) that inequality benefits growth in rich countries but retards it in poor ones, but over 20-year periods, as opposed to his original finding, which considers 10-year periods. This finding is not consistent with the original work on the relationship between inequality and growth that addressed the long-run and found a negative association (Benabou, 1996; Alesina and Rodrik, 1994; Persson and Tabellini, 1994; Perotti, 1996), but can be seen as complimentary to Chen (2003), who using a cross-sectional approach finds an inverse-U relationship over similar periods. Finally, in the very long-run (37 years) the effect of inequality on growth becomes linear and negative. Thus, it seems that in the short and medium-run the relationship between inequality and growth has an inverted-U shape. In the long-run this relationship changes and depends on the level of income, while in the very long-run it becomes linear and negative.

The structure of the paper is as follows. In the next section, I discuss the main theoretical arguments that explain the relationship between inequality and growth and review the previous empirical exercises, as well as their potential limitations and what might be considered the current dominant view. In Section 3, I present the data followed by the estimation strategy. In the next section, I present the results for the different time periods. Section 5 concludes.

2 Literature Review

The debate about the relationship between inequality and economic growth has a long story in the economic literature. Starting with the work of Kuznets (1955, 1963), many distinct arguments have been put forward about the causal direction between these two variables and the effects between them. Here, I focus on the effects of inequality on growth.

From a theoretical perspective, most existing arguments favor either a positive or a negative effect of inequality on growth. Following Barro (2000), these arguments can be classified in four categories: credit-market imperfections, political economy, social unrest, and saving rates.

The impact of inequality on growth through credit-market imperfections is based on the role of credit markets on linking savings and investment decisions across households. Access to credit-markets, however, is dependent on satisfying a given level of assets and/or income. With imperfect credit-markets, poor households may not be able to exploit high-return opportunities such as human capital investment. If this is the case, inequality-reducing transfers may lead to a larger investment in human capital, which in turn would lead to increased economic growth (Perotti, 1996). Through this mechanism we would thus observe a negative relationship between inequality and growth (Galor and Zeira, 1993; Galor and Moav, 2006). Barro (2000), however, points out that if the impact of human or physical capital on growth requires a certain minimum threshold (e.g. secondary education has a significant impact on subsequent growth, but not primary education), then lowering inequality could reduce the type of investment required for growth, negatively affecting it. Hence, the argument based on credit-market imperfections can actually support both a negative as well as a positive effect of inequality on growth.

The political economy argument focuses on the distortionary effects of redistributive policies. If a country's mean income is larger than the median income, a system of majority voting would favor redistribution from the rich to the poor. These transfers, however, would tend to distort economic decisions and hence, have a negative impact on investment. Through this channel, an increase in inequality would lead to lower investment, and thus lower economic growth.[2] Barro pushes this argument one step further based on the idea that in a highly unequal society political power also tends to be highly skewed. If this is the case, the rich may divert resources into stopping transfers to occur in the first place. A higher level of economic inequality would imply a higher need for the rich to invest resources in lobbying and influencing political decisions. Because these activities are costly, higher inequality would thus have a negative impact on subsequent growth even if no actual redistribution occurs.

The idea underlying the social unrest argument is that if a society is highly unequal, the poor are more prone to engage in crime, protests, and disruptive activities in general. The resources thus used are diverted from other more productive activities and, at the same time, create more

[2] Saint-Paul and Verdier (1993) argue to the contrary that if redistribution leads to increased spending *in education*, then it can actually have a positive effect on growth.

uncertainty (Alesina and Perotti, 1996). The effect is that investments gets negatively affected and hence inequality should have a negative impact on growth.

One argument that favors a positive relationship between inequality and economic growth relies on the idea that marginal saving rates tend to rise with the level of income. If so, an increase in inequality would raise the aggregate saving rate, thus increasing investment and growth.

In addition, there exists a general argument not mentioned by Barro (2000) according to which some level of inequality is required for people to have an incentive to invest in human and physical capital, which are important contributors to long-run growth. This argument, however, has not been greatly emphasized in the literature, possibly because it is not clear the levels for which it is relevant.

All these arguments imply a linear relationship between inequality and growth. As was first shown by Banerjee and Duflo (2003), however, it seems that this relationship is indeed non-linear, possibly because these mechanisms do not act in isolation. Banerjee and Duflo propose a model that leads to an inverse-U relationship based on the idea of a hold-up problem. In their model, there are two groups, one of which (chosen randomly) can hold up aggregate growth by supporting a growth-enhancing opportunity conditional on the other group transferring a fraction of its income. The latter, in turn, can agree to make the transfer or decide not to do so. If it decides not to make the transfer, the growth opportunity is lost, while, if it makes the transfer, the time and cost of the bargaining process imply that the economy benefits only by a fraction of the potential growth opportunity. The non-linearity arises because the condition under which the poorer group demands a transfer is more easily satisfied when inequality is higher, while the condition for the richer group is more easily satisfied when inequality is smaller. Since a demand for transfers by either group translates into lost growth, it thus follows that both increases or decreases in inequality can lead to less growth.

At the theoretical level, therefore, we have a mixture of arguments that do not lead to a definite conclusion regarding the effects of inequality on growth. Table (1) summarizes these results.

Table 1: **Theories on the Effect of Inequality and Growth**

Theory	**Predicted Relationship**
Credit-market imperfections	Negative, uncertain
Political economy	Negative
Social unrest	Negative
Saving rate	Positive
Accumulation incentives	Positive
Hold-up	Inverse-U

Let me now turn to a discussion of the empirical work. At this level, the relationship between inequality and growth is also not clear. Estimating the impact of inequality on growth has proven to be a difficult endeavor due to the limited availability of data as well as the problem of reverse causality, which makes it hard to find appropriate estimation techniques given the absence of an appropriate instrumental variable for inequality. The only exception is Easterly (2007), discussed below. I next present a brief review of the empirical evidence emphasizing the existing problems and limitations.

Regarding the quality of the data, most studies conducted during the 1990's (Benabou, 1996; Alesina and Rodrik, 1994; Persson and Tabellini, 1994; Perotti, 1996) find a negative association between inequality and growth over a 20-30 year period. However, they suffer from various limitations. First, many of the estimates of a significant negative relationship between inequality and growth are not robust to sensitivity analyses. Indeed, Deininger and Squire (1998) question the validity of this association since adding additional regressors or regional dummy variables to the original specification renders the estimates on inequality insignificant. One reason is that these studies rely on limited data sets in terms of regularity, coverage and consistency. Data on inequality used to be sparse, both in time and space, providing observations only at a given point in time and for a small set of countries.

Second, measurement error is generally a concern in cross-country studies. Countries may have different definitions for the variables of interest and the accuracy of the data may also differ. Among the different variables, however, inequality is especially prone to measurement error, which can lead to a significant bias in the estimation results if this measurement error is systematically correlated with other variables in the regression. While the direction of the bias is unknown ex-ante, a spurious negative association between inequality and growth could result if, for instance, more unequal countries tend to underreport their inequality statistics and at the same time tend to grow more slowly than similar countries. Furthermore, many of these data points were derived from estimations based on national accounts, which later on were shown to provide a quite inaccurate picture of the countries' inequality profiles (Deininger and Squire, 1996).

Third, omitted-variable bias can also represent a problem. While the direction of the bias is again not clear ex-ante, the absence of structural parameters, like for instance the level of corruption may bias the coefficient on inequality (omitting the level of corruption would generate a negative bias in the inequality coefficient since it is positively correlated with inequality, but negatively correlated with growth).

Regarding the econometric techniques, the work that concludes that inequality is detrimental to growth was based exclusively on cross-sectional analyses. These studies do not answer the policy relevant question of how changes in a country's level of inequality relates to changes in *that* country's growth; instead, the only conclusion that we can draw from the cross-country regressions is that "there is a long-term pattern according to which countries with lower levels of inequality tend to grow faster". To address the policy-relevant question, we need to resort to panel estimation.

The problem of measurement error was first tackled by Deininger and Squire (1996), who constructed a broad-based inequality dataset with a panel structure, which has been used in every study thereafter including Li and Zou (1998); Forbes (2000); Barro (2000); Banerjee and Duflo (2003), and Chen (2003). To exploit the panel structure of this dataset, most of these papers implement panel-data approaches, which in principle also allow to control for heterogeneity bias. However, these papers use different empirical strategies and also reach quite different conclusions, as I discuss next.

Using fixed effects and random effects estimation Li and Zou (1998) find a positive association between inequality and growth over 5-year periods. In a further attempt to control for the endogeneity between inequality and growth, Forbes (2000) uses the basic Arellano-Bond estimator applied to 5-year periods, and also finds a robust positive association. Li and Zou (1998), however, also replicate previous cross-section results (Alesina and Rodrik, 1994; Persson and Tabellini, 1994) for growth over the 30-year period between 1960-1990, confirming the findings of a negative relationship between inequality and growth. This long-run result is further confirmed by Easterly (2007), who instruments for inequality by using the abundance of land suitable for growing wheat relative to that suitable to grow sugarcane. Furthermore, Easterly finds that inequality also negatively affects institutional formation and human capital accumulation; both key factors in the process of development.

On the other hand, Barro (2000) argues that running fixed effects regressions tends to exacerbate the biases due to measurement error because of the implicit differencing. Barro's argument relies on the fact that measures of inequality do not tend to vary a great deal over time for particular countries, and hence the need to exploit the cross-country variation. Using a three-stage least squares (3SLS) estimator that effectively treats the country-specific error terms as random he finds a negative association between inequality and growth over 10-year periods, but only for poor countries. Among rich countries, he finds that inequality encourages growth over this time frame. Forbes points out, however, that the important policy question is "how a change in a country's level of inequality will affect growth within that country" (Forbes, 2000, p. 870). Thus, an alternative approach is to try to reduce the measurement error associated with inequality and estimate the effect using fixed-effects-like regressions. As I argue below, much progress has been made in improving the quality of inequality measures and in compiling them across countries and over time, which provide a justification for this alternative approach.

The positive association between inequality and growth found by Li and Zou, and Forbes is not necessarily inconsistent with the negative relationship found in the *long-run* in previous studies. However, as Forbes (2000, p. 885) points out, "it is also possible that the within-country and cross-country relationships between inequality and growth work through different channels and are of opposite signs". Indeed, Halter et al. (2010) argue that inequality has a mostly positive effect in the short-run because the economic mechanisms dominate over this time frame; but, it has a mostly negative effect in the long-run because the social and political mechanisms operate here. As I show below, it seems that indeed there is a turning point at which the relationship changes.

Following the most recent literature, it is also possible that these results emerge because the basic regression is misspecified. In particular, while the two sets of studies discussed so far find opposing results, they share the caveat that they assume that inequality and growth are linearly related. As Banerjee and Duflo (2003) point out, however, there is no reason ex-ante to model the relationship between inequality and growth as a linear one. To test for nonlinearities, they first include a quadratic term on the change in inequality and, second, they use a kernel regression. In both cases they find evidence of an inverse-U association between *changes* in inequality and growth in the short-run (5-year periods). While this result gives a completely different flavor to the study of inequality and growth, it is not directly comparable to the other work since it refers to a relationship between growth (i.e., changes in income per capita) and changes in inequality, as opposed to previous inequality, which is the usual approach in the literature.[3]

In the long-run, the previous consensus of a negative relationship between inequality and growth has also been challenged. Using a standard cross-section regression, Chen (2003) finds evidence of an inverted-U relationship between inequality and growth. However, using a similar approach, Bleaney and Nishiyama (2004) find no support for this once they incorporate additional regressors. Depending on the specific set of controls, they find that the sign on inequality changes and in one case it even becomes positive and significant. Furthermore, they also find no support for Barro's finding that increased inequality retards growth in poor countries but encourages it in rich ones. Bleaney and Nishiyama (2004) argue that their results are inconsistent with Barro's. However, because Barro considers 10-year periods, the fact that Bleaney and Nishiyama analyze a 25-year period implies that the two results are not directly comparable. Also, Bleaney and Nishiyama do not include a quadratic term on inequality and thus their analysis is subject to the criticism posed by Banerjee and Duflo.

In this paper, I favor system-GMM estimators that control for time-invariant country effects and that emphasize within country variation and thus address the policy-relevant question discussed above. In particular, I use a similar estimation strategy as the one proposed by Forbes (2000), who in turn uses the same specification as Perotti (1996), but with a panel-data structure. In addition, I incorporate several recent improvements to the original Arellano and Bond (1991) estimator used by Forbes. While the Arellano and Bond estimator allows a large degree of flexibility to estimate the effect of inequality on growth, further econometric work has shown its possible limitations and provided potential solutions. The main caveat of the difference-GMM estimator is that it may suffer from the problem of "weak instruments", rendering very imprecise estimates.[4] Arellano and Bover (1995) and Blundell and Bond (1998) propose a system GMM that, based on Monte Carlo simulations, seems to provide more consistent and efficient estimates. This added efficiency comes at the cost of imposing an additional moment condition.

Later work has also shown that the standard errors of both estimators are systematically downward biased, especially when the instrument count is high. Windmeijer (2005) proposes a small-sample correction that deals with this problem.

[3]In the sensitivity analysis conducted by Forbes (2000), she includes a quadratic term, but it turns out not to be significant.

[4]In this paper I use the terms difference-GMM, first-difference-GMM and Arellano and Bond estimator indistinctly.

Even after the correction, however, there remains an issue related to the number of instruments used by either the difference-GMM or the system GMM. Both estimators face a problem of instrument proliferation that can "overfit" the endogenous variables, leading to biased estimates. This is particularly problematic when the time dimension starts to increase, as is the case in this paper. A way to limit this problem is to reduce the instrument count (hence sacrificing efficiency for consistency), which I do for all time frames analyzed in this paper. The problem is that both the difference-GMM and the system-GMM estimators were originally constructed to be applied in panel data that strictly satisfy the small T, large N assumption. Altonji and Segal (1996) and Ziliak (1997) show that, if this assumption is not satisfied, the bias of the GMM estimators increases significantly as the number of moment conditions increases, leading to (downward) over-fitting bias. Stated in simple terms, in the context of the relationship between inequality and growth the problem is that the number of instruments in both the difference-GMM and system-GMM increases more than proportionally with the number of periods T, leading to bias.

There are two general approaches to reduce the number of instruments: i) Reduce the possible lags that can be used as instruments, and ii) Impose a more restricted application of the moment conditions (each of them corresponding to all available time periods), as in Calderon et al. (2002). Following Ziliak (1997) this amounts to stacking the matrix of instruments into a reduced matrix. Below, I use both approaches to reduce the number of instruments of the system-GMM estimator and identify the effect of inequality on growth in the short and medium-run.

Finally, Hauk and Wacziarg (2009) show in the context of cross-country growth regressions (that do not include inequality) that fixed-effects and the difference-GMM estimators tend to overestimate the speed of convergence and to underestimate the effect of several common determinants of growth, including human capital. They show that the system-GMM estimator corrects for these problems and also greatly reduces classical measurement error bias. And, while this estimator may be biased if the required moment conditions are not satisfied, they argue that "because of its desirable properties in addressing the weak instruments problem, [it] may still be a good estimator in practice for small samples" (Hauk and Wacziarg, 2009, p. 110).

The core of the paper deals with these problems and incorporates the improved data set for inequality as well as longer time-series for the rest of the variables.

3 Empirical Approach

In this section I discuss the data used and the empirical strategy.

3.1 Model

The objective of this paper is to estimate the effect of inequality on subsequent economic growth over different time frames. To this end, I follow Forbes (2000) and Perotti (1996) in choosing a parsimonious approach within what Perotti calls an "income-distribution-augmented-growth equation" (p. 158). Growth is estimated as a function of initial income pre capita, inequality, inequality squared to control for possible nonlinearities, human capital, market distortions and country and period dummy variables. Except for the dummy variables and the quadratic term, this model is identical to the one used by Perotti (1996) and is a standard starting-point in the growth literature. Country dummies are added to control for time-invariant omitted-variable bias, while period dummies are included to control for global shocks, which are not captured by the regressors, but may affect aggregate growth. From an econometric perspective, country dummies allow for the intercept to vary across countries and period dummies allow for the intercept to vary over time.

I prefer this model first because it allows for comparability with existing literature. In particular, any discrepancy between this study and previous ones cannot be explained by differences in model specification, Also, a need for parsimony. The simple specification helps maximize the degrees of freedom, which is important in this case since sample size is limited by the availability of data on inequality and because of the use of panel data. Finally, the use of stock variables measured at the start of the period (as opposed to flow variables measured throughout the periods) should help reduce the problem of endogeneity. Furthermore, this specification is supported by recent work. In 2004, Sala-i Martin, Doppelhofer, and Miller looked at the robustness of 67 different explanatory variables in cross-country growth regressions. They find that the likelihood of a variable "belonging to the true model" is the highest for the relative price of investment, primary school enrollment and the initial level of income per capita.[5] In particular, using a Bayesian Averaging of Classical Estimates (BACE) they find that these variables have the highest posterior inclusion probability among the 67 variables studied.[6]

The model is thus the following:

$$\begin{aligned} \Delta Y_{it} &= \beta_1 I_{i,t-1} + \beta_2 f(I_{i,t-1}) + \beta_3 Y_{i,t-1} \\ &\quad + \beta_4 Meduc_{i,t-1} + \beta_5 Feduc_{i,t-1} \\ &\quad + \beta_6 PPPI_{i,t-1} + \alpha_i + \eta_t + \mu_{it} \end{aligned} \tag{1}$$

where i represents each country and t represents each period; ΔY_{it} represents average annual growth for country i during period t; $I_{i,t-1}$, $f(I_{i,t-1})$, $Y_{i,t-1}$, $Meduc_{i,t-1}$, $Feduc_{i,t-1}$ and $PPPI_{i,t-1}$ are respectively inequality, a function of inequality which in this paper will take the form of either a quadratic term on inequality or an interaction term between inequality and income, i.e., $f(I_{i,t-1}) = I^2_{i,t-1}$, or $f(I_{i,t-1}) = I_{i,t-1} * Y_{i,t-1}$, income per capita, male and female education, and a measure of market distortions for country i in period $t-1$; α_i are country dummies, η_t are period dummies and μ_{it} are the errors.

[5] Sala-i Martin et al. (2004) consider primary school enrollment as a measure of human capital, as opposed to Perotti (1996), Barro (2000) and Forbes (2000) who use years of secondary schooling.

[6] The BACE approach combines diffuse priors with averaging of OLS estimators across models.

3.2 Data

In model (1), Y is the natural log of real GDP per capita and ΔY is its difference, averaged by the number of years in each period. I is measured by the Gini coefficient, $Meduc$ and $Feduc$ are measured by male and female average years of secondary schooling in the population aged over 25, and $PPPI$ is the price level of investment.[7] Estimation is based on 5-year, 10-year, 20-year periods and a very long-run cross-section estimation over a 37-year period. In all specifications the dependent variable is average growth of real GDP per capita and the regressors are taken from the last year available in the previous period. Available data covers the period 1950-2007.

Data on human capital is drawn from Barro and Lee (2010), which is the latest update on the original Barro and Lee (1993) database on educational achievement. Income per capita and the measure of market distortions (price level of investment, PPPI) come from the Penn World Tables 6.3 (Heston et al., 2009). Finally, inequality statistics come from the UNU-WIDER World Income Inequality Database. This extended data set incorporates a systematic improvement on the inequality observations, which now includes more countries and a more precise quality classification. Summary statistics for each time frame are presented in Appendix B. Since an important contribution of the paper is the use of a larger, more consistent dataset on inequality, in the next subsection I discuss it in more detail.

3.2.1 UNU-Wider Inequality Data Set

One of the main problems in analyzing the relationship between inequality and growth is the quality of the data. Before 1996, this work was limited to cross-sectional analyses mainly because of the limited availability and quality of the inequality data. In 1996, Deininger and Squire put together a consistent and comprehensive inequality data set with a panel structure that has several consecutive measures of income inequality for each country. They also constructed a "high-quality" data subset that included an observation only if it satisfied the following criteria: i) it must be based on household surveys (as opposed to national accounts, which was the previous practice in many countries), ii) it must be based on a comprehensive coverage of the population, and iii) it must be based on a comprehensive coverage of income sources, including income from self-employment, non-wage earnings and non-monetary income. This high-quality dataset was aimed specifically at reducing the problem of measurement error that had been prevalent in previous research. Furthermore, even this restricted dataset included a larger set of countries and of observations than in any previous data compilation.[8]

[7] This variable measures the cost of investment in a given country relative to the United States and is calculated as the purchasing power parity (PPP) over investment normalized by the exchange rate relative to the United States.

[8] Deininger and Squire (1996) compiled a total of around 2,600 observations, but only 682 satisfied the 3 criteria mentioned above.

The panel data structure of the inequality data set is specially important because it allows for the use of panel data techniques. Panel estimation provides a way to control for unobserved time-invariant country characteristics, thereby removing any source of correlation between these unobservable characteristics and the explanatory variables. One caveat, however, is that this technique does not control for unobservable variables that do change over time. As the period of analysis increases, this limitation becomes more important since it is less likely that the unobserved variables remain constant. This caveat should be taken into consideration in all the panel-based estimations presented below.

After the original work by Deininger and Squire (1996), the World Institute for Development Economics Research at the United Nations University embarked on a systematic effort to expand and improve upon this dataset. Thus, the UNU-WIDER World Income Inequality Database was created. The approach of the UNU-WIDER database is slightly different from that of Deininger and Squire (1996). In particular, this database does not automatically classify an observation as "high-quality" or "low-quality" according to the criteria mentioned above. However, it includes the necessary information to decide whether or not to filter the data. In addition, the UNU-WIDER database also provides a new quality scale ranging from 1 for high-quality to 4 for low-quality, according to the following criteria: i) the concepts underlying the observations are known, i.e., it is specified whether inequality is measured using income (gross or net), consumption, etc., ii) the coverage of the income/consumption concept relies on the most preferred set of underlying definitions, which is analogous to the second requirement of Deininger and Squire (1996), i.e., that the coverage of income sources is comprehensive,[9] and iii) the quality of the survey (mainly coverage issues, questionnaires and data collection methodology) is sound.

The UNU-WIDER database thus allows for a more precise classification of the inequality measures in terms of "high-quality". This seems particularly important considering that "[a] reexamination of the sources of [Deininger and Squire (1996)] revealed several instances of mistakenly labeled "good quality estimates", i.e., that did not, in fact, meet the criteria that had been set up" (UNU-WIDER, 2008a, p. 13). Consistent with this statement, I find for instance that for the 180 "high-quality" inequality observations used by Forbes (2000), which come directly from the Deininger and Squire dataset, only 13% have a classification of 1, 21% have a classification of 2, 36% one of 3, and 3% one of 4. The remaining 27% was not found on the UNU-WIDER database implying that they had been replaced by better quality data (due to revisions in the construction of the database or updates in the primary sources used to construct it).[10] Thus, while Deininger and Squire (1996) constructed a much

[9]The only exception is that "[f]or most developed countries, estimates based on monetary incomes have been accepted since the inclusion of in-kind incomes and home production does not have a major effect on the income distribution" UNU-WIDER (2008a).

[10]A similar account is true for other studies that include the whole Deininger and Squire dataset. Forbes's dataset is smaller due to the more stringent data requirements needed to run the Arellano-Bond estimator.

better inequality dataset to what was available previously, the UNU-WIDER inequality database has made further significant improvements to it.

The UNU-WIDER data set includes 5313 observations on the Gini coefficient for 159 countries, most of them from 1960 to 2006.[11] The database includes more than one observation per country per period. Since inequality statistics are not available every year, I take the latest observation available within the previous period. But, even after reducing the dataset in this way, in many cases there is still more than one statistic available for each period. Hence, I applied the following procedure in order to choose a single observation for each country period, which relies on sequentially eliminating observations according to whether or not they satisfy the following criteria, in the specified order:[12]

1. Data comes from surveys; i.e., data points based on national accounts are not taken into account.[13]
2. The coverage is national, includes all people and all ages.[14]
3. The quality index is the highest available.[15]
4. The measure of inequality is consistent across periods for a given country; i.e., I try to have all inequality observations for a given country based on the same concept (income or consumption/expenditure).[16]
5. The source is consistent across periods for a given country; i.e., following the recommendation of UNU-WIDER (2008a), I try to have as many observations as possible from the same source.

To reduce the problem of measurement error, I use only observations with a quality of 1, 2 and 3, i.e., I drop observations with a quality of 4. Also, since I apply a first-difference-based GMM estimator, I keep a country only if it has inequality observations for at least two consecutive periods. Finally, because consumption-based inequality measures tend to be systematically lower than income-based measures, following Deininger and Squire (1996), I add 6.6 points to the Gini coefficients based on consumption/expenditure in order to make them comparable to the ones based on income.

Applying these criteria to the available data in the UNU-WIDER database, I end up with a sample of 100 countries and 554 observations for the basic 5-year specification.

[11] The latest update of this database was made in May, 2008. The current version is V2.0c.

[12] Atkinson and Brandolini (2009) point out the dangers of picking data points from the UNU-Wider inequality dataset. While I followed the specified procedure as closely as possible, a few arbitrary decisions were made. I present detailed tables with the used inequality data at the end of the paper.

[13] This is the same as Deininger and Squire's first requirement.

[14] This is the same as Deininger and Squire's second requirement.

[15] This incorporates Deininger and Squire's third requirement plus the specific classification criteria used by UNU-WIDER.

[16] In addition, because the inequality statistics based on income are not adjusted, in general I prefer income-based observations rather than consumption/expenditure-based observations.

3.2.2 Analysis over different time spans

The latest update to the original Barro and Lee (1993) dataset on education makes it possible to construct a dataset for the period 1950-2007 for 100 countries. This allows me to run panel regressions for 5, 10 and 20-year periods, which I denote short-run, medium-run and long-run, respectively. Growth is averaged over at least 5-year periods in order to avoid short-run disturbances and reduce serial correlation from business cycles. In each period, growth is regressed on the lagged values of the explanatory variables measured at the latest (available) year of the previous period. I also run a cross-sectional regression over a 37-year period, which I denote the very long-run. This regression serves as a reference point for the relationship between inequality and growth, but, strictly speaking, it is not directly comparable to the panel-based regressions. Nevertheless, it is the first time that a cross-country regression analyzing the role of inequality looks at such a long period of time.

3.3 Econometric identification and estimation

In order to determine the optimal econometric approach to estimate equation (1), we need to consider the specifics of the model. For convenience, I rewrite it here with a slight modification. Noting that $\Delta Y_{it} = Y_{it} - Y_{i,t-1}$, equation (1) can be written as:

$$\begin{aligned} Y_{it} &= \beta_1 I_{i,t-1} + \beta_2 f(I_{i,t-1}) + \gamma Y_{i,t-1} \\ &\quad + \beta_4 Meduc_{i,t-1} + \beta_5 Feduc_{i,t-1} \\ &\quad + \beta_6 PPPI_{i,t-1} + \alpha_i + \eta_t + \mu_{it}, \end{aligned} \tag{2}$$

where $\gamma = \beta_3 + 1$.

There are at least four issues that complicate the estimation of this model: i) *Endogeneity*: Because causality between inequality and growth may run in both directions, inequality may be correlated with the error term (even when all regressors are lagged), ii) *Heterogeneity effects*: It may be that country-specific characteristics are correlated with the explanatory variables, iii) *Measurement Error*: As we discussed before, one of the main problems in trying to discern the impact of inequality on growth is that inequality is measured with error, and iv) *Autocorrelation*: The presence of the lagged dependent variable on the right-hand-side gives rise to autocorrelation.

Standard methods of panel estimation are random effects and fixed effects.[17] Random effects are more efficient since they incorporate information from variation across countries and time; fixed effects, on the other hand, only incorporate variation within countries as they are based on the within transformation. The main caveat of using random effects is that it is consistent only if the individual specific effect is uncorrelated with the other covariates. However, the main reason for including country effects α_i in model (1) is precisely because we think that there are structural factors specific to each

[17] Here I follow the terminology used in the econometric literature, but I emphasize that in both cases the individual specific effects are considered to be random (Cameron and Trivedi, 2005).

country that may affect the relationship between inequality and growth, i.e., that may be correlated with the other explanatory variables. Therefore, in principle, a fixed effects approach would seem appropriate. However, both fixed effects and random effects are inconsistent in the presence of a lagged dependent variable $Y_{i,t-1}$ like in model (1), as shown in equation (2).

The estimator developed by Arellano and Bond (1991) provides a better framework to estimate model (1). However, several studies (e.g. Harris et al. (2008)) have shown that this estimator suffers from the "weak instrument problem". And, furthermore, that it tends to provide biased estimates (Hauk and Wacziarg, 2009). The system-GMM estimator proposed by Arellano and Bover (1995) and Blundell and Bond (1998) solves these problems at the cost of imposing an additional moment condition. However, the system-GMM estimator presents another problem that becomes increasingly significant as T increases: instrument proliferation. Because both the difference-GMM and the system-GMM estimators use second and further lagged values of regressors as instruments, the number of instruments increases significantly as the number of periods in the panel increases. This renders the usual Sargan-Hansen test of overidentifying restrictions invalid. Practitioners have opted to reduce the number of instruments by either reducing the number of lags allowed or to collapse the matrix of instruments. I discuss all these issues in detail in Appendix A.

4 Results

In this section I discuss the main results of the paper. In the first subsection I run regressions for 5 and 10-year periods. I show that the results are consistent with Banerjee and Duflo (2003) in that the association between inequality and growth has an inverse-U shape. These results contradict Li and Zou (1998) and Forbes (2000), even though I use similar approaches. The differences are due to the lager dataset and the fact that I use s system-GMM estimator. In the next subsection I present the results for the 20-year regression and show that at this length there is a fundamental change in the relationship between inequality and growth. The results are similar to Barro (2000) in that higher inequality tends to negatively affect growth in poor countries, but to positively affect it in rich ones. This contradicts previous evidence of a linear negative relationship across the board over similar time frames (Alesina and Rodrik, 1994; Persson and Tabellini, 1994), and it also complements the result of Chen (2003), who finds an inverse-U relationship.

4.1 Short and Medium-run: An Inverse-U Relationship

Here I present the results of estimating model (1) using the extended inequality data set as well as the system GMM estimator with the small sample correction and instrument reduction.

Table (2) summarizes the results of the set of regressions for 5-year periods. I report estimates based on fixed effects (column (1)), random effects (column (2)), Arellano and Bond (column (3) is the one-step difference-GMM, while column (4) is the two-step robust difference-GMM, which incorporates the Windmeijer (2005) correction). Columns (5)-(9) report the results using different versions of the system GMM estimator that control for instrument proliferation. The system GMM with the full set of instruments is reported in column (5). This specification has 396 instruments. Column (6) allows for only two-lags of each variable in the instrument set for each period (leading to 181 instruments), while in Column (7) I only allow for one-lag (leading to 131 instruments). Column (8) presents the estimates resulting from the application of collapsing the matrix of instruments as in Calderon et al. (2002). It now includes 77 instruments. The last column combines both approaches and thus is the most restrictive (it has only 29 instruments).

Before analyzing the results, I briefly discuss the Hausman test, which influences the choice of estimation technique, as well as some additional tests on the assumptions of the model: i) No serial correlation (Assumption (**??**)), and ii) Validity of instruments (Hansen and difference-in Sargan tests).

There is significant variation in the results depending on the estimation procedure used. In order to determine whether a random-effects approach is appropriate, I conduct a Hausman test comparing the fixed-effects estimates of column (1) and the random-effects estimates of column (2). The test statistic is $\chi^2_{(15)} = 78.51$, which rejects the null hypothesis of no difference between the two estimates at any standard level of significance, thus favoring fixed effects.

Regarding Assumption (**??**), the problem is that the presence of serial correlation in μ_{it} would invalidate the use of lagged values of the endogenous variable as instruments. Arellano and Bond (1991) construct a test statistic m_2 to test for second-order serial correlation based on the residuals from the first-difference equation.[18] As can be seen from the p-values, I am unable to reject the null hypothesis of no second-order serial correlation (although marginally so in columns (5)-(7)). Alternatively, we can use a Hansen test of overidentifying restrictions (OIR).[19] Bowsher (2002), however, shows that as the number of moment conditions (and therefore the number of instruments) increases, the Hansen test tends to be very undersized and to possess extremely poor power properties. In the case at hand, indeed, the Hansen test gives p-values of 1.00 in columns (4)-(6) in Table 2. Such high p-values attest the loss of power of the test, and imply that the number of instruments is potentially large. Note that while the problem of instrument proliferation applies to both estimators, the difference-GMM and the system-GMM, it is more serious for the latter because it includes levels and differences as instruments, while the Arellano and Bond estimator only incorporates differences as instruments. Thus, while the

[18]The logic of the test is the following. If the μ_{it}'s are serially uncorrelated, then the disturbances in the differenced model, $\Delta\mu^*_{i,t} = \mu^*_{it} - \mu^*_{i,t-1}$, follow an MA(1) process and thus are correlated of order 1, but not correlated of order 2. On the contrary, if the disturbances $\Delta\mu^*_{i,t}$ are correlated of order 2, it means that $\mu^*_{i,t}$ are correlated. The test statistic m_2 is asymptotically distributed as $N(0,1)$.

[19]The intuition of this test is that when a model is overidentified (i.e., when we have more instruments than parameters to be estimated), we can run a test on the original moment condition for the GMM estimator, which accounts for a test of the exogeneity of instruments. When the model is just identified, this moment condition is identically equal to zero. But, when the model is overidentified, the moment condition is not necessarily equal to zero and a test can be constructed.

Table 2: **Regression results: Short-run**

Estimation Method	FE (1)	RE (2)	AB (3)	RAB (4)	System GMM Full (5)	2 lags (6)	1 lag (7)	C (8)	C, 1 lag (9)
Income	-0.0340***	-0.0067***	-0.0495***	-0.0544***	0.0007	0.0025	0.0018	0.0223**	0.0351***
	(5.34)	(2.65)	(8.32)	(4.21)	(0.19)	(0.65)	(0.51)	(2.52)	(3.43)
Inequality	0.1103	0.0539	0.2488**	0.2282	0.1300	0.1250	0.1090	0.5624**	0.4783**
	(1.03)	(0.65)	(2.49)	(1.61)	(1.25)	(0.94)	(0.91)	(2.36)	(2.02)
Inequality^2	-0.0519	-0.0795	-0.2198*	-0.2000	-0.1897	-0.1828	-0.1594	-0.5740**	-0.4723*
	(0.45)	(0.86)	(1.88)	(1.36)	(1.59)	(1.29)	(1.23)	(2.54)	(1.97)
Female	0.0022	-0.0014	0.0134*	0.0166	-0.0078	-0.0121	-0.0163**	-0.0128	-0.0262**
Education	(0.33)	(0.37)	(1.85)	(1.43)	(1.08)	(1.49)	(2.09)	(1.37)	(2.47)
Male	0.0033	0.0067*	-0.0077	-0.0096	0.0103	0.0138	0.0183**	0.0057	0.0119
Education	(0.46)	(1.84)	(1.08)	(0.84)	(1.60)	(1.65)	(2.17)	(0.55)	(1.02)
PPPI	-0.0001	-0.0001	-0.0001*	-0.0001	-0.0001**	-0.0002**	-0.0001	-0.0003***	-0.0005***
	(1.50)	(1.56)	(2.08)	(1.34)	(2.18)	(2.45)	(1.48)	(2.63)	(3.34)
Countries	100	100	100	100	100	100	100	100	100
Observations	554	554	399	399	554	554	554	554	554
Instruments			331	331	396	181	131	77	29
Arellano-Bond test (p-value)			0.426	0.234	0.050	0.058	0.063	0.244	0.171
Hansen test (p-value)				1.000	1.000	1.000	0.098	0.350	0.394
Diff-in Sargan test (p-value)					1.000	1.000	1.000	0.113	0.628

Note: Dependent variable is average annual per capita growth. Period dummies are not reported. t statistics are shown in parenthesis. Column (1) reports fixed-effect estimation, and column (2) reports random-effects estimation. Column (3) is the one-step Arellano and Bond estimator. Column (4) is the two-step Arellano and Bond estimator with the Windmeijer finite sample correction, columns (5)-(9) are the robust system-GMM estimator. Column (5) includes the full set of instruments. Column (6) allows instruments for up to 2-lags and column (7) allows for only 1 lag. Column (8) collapses the matrix of instruments. Column (9) provides the most restrictive specification: a collapsed matrix of instruments with only a 1-period lag. Significance: * significant at 10%; ** significant at 5%; *** significant at 1%.

system-GMM estimator has good properties in terms of reducing the problem of weak instruments that the difference-GMM has, it can easily lead to a problem of instrument proliferation. That is the main reason why I have included specifications which constrain the number of instruments in columns (6)-(9).

Reducing the lags allowed for the instruments does not seem to help solve the problem of instrument proliferation: the Hansen test remains at 1.00 in column (6) and the difference-in Sargan test remains at 1.00 in columns (6) and (7).[20] Collapsing the matrix of instruments, as in Calderon et al. (2002), however, does reduce the problem. The regressions in columns (8) and (9) in Table (2) thus provide more plausible values for both the Hansen test and the difference-in Sargan test. Also, the Arellano and Bond test of no serial correlation is barely satisfied in the specifications with the full set of instruments or with limited lags, but it is satisfied in the 2 specifications that collapse the matrix of instruments.

My preferred specification for the 5-year period analysis is column (8), which collapses the matrix of instruments leading to a total of 77 instruments. I discuss the corresponding results next. Summary statistics for the data used in the regressions in Table (2) as well as a list of all the Gini coefficients is presented in Appendix B, Tables 7 and 11.[21]

First, inequality and growth are related in an inverse-U shape, i.e., either a high or a low level of inequality tend to negatively affect growth. This implies that there exists an optimal inequality level, which according to this specification occurs at a Gini coefficient of 49 (column 8).[22] The coefficient also imply that the effect of inequality is economically significant. For instance, if a country with a Gini coefficient one standard deviation away from the mean changes it by one standard deviation, that country will experience on average a 0.35% change in annual growth. Of course, the effect becomes stronger as we move further toward the extremes of the distribution.

Interestingly, the positive and significant coefficient on initial income shows that there may be *divergence* in the short-run, i.e., richer countries tend to grow faster than poorer ones. Also, comparing the different columns I find evidence confirming the finding of Hauk and Wacziarg (2009), who argue that fixed-effects and the Arellano-Bond estimators overestimate the speed of convergence. Indeed, using either fixed-effects, the Arellano-Bond estimator or the robust Arellano-Bond estimator, the coefficient on initial income is negative and significant, which would imply the existence of convergence

[20] The difference-in Sargan test provides an overidentification test for the validity of the additional instruments used by the system-GMM estimator, i.e., the levels.

[21] The Gini coefficients used in the regressions and for the summary statistics are defined over the range 0-1; however, in the tables that present the Gini coefficients I show actual Gini coefficient over the range 0-100.

[22] Note that the sign of the coefficients on inequality and inequality squared required for an inverse-U relationship are the correct ones in all specifications, but they are significant only in the most restrictive ones. This differs from the results found with the database used by Forbes (2000). When I run the same regression with her data (not reported), the quadratic term on inequality is never significant.

in the short-run. However, this result is reversed for all specifications using the system-GMM (i.e., the coefficient on initial income is positive), and it becomes significant in the preferred specification.

The measure of market distortions (PPPI) is consistently negatively correlated with subsequent growth, and significant in the preferred specification. Finally, increasing female education seems to retard growth in the short-run (but the effect is not significant), while increasing male education has a positive effect (but again, not significant). These results might seem counterintuitive. However, a positive coefficient for male education and a negative one for female education, even if not significant in most specifications, are consistent with previous work (e.g. Barro and Lee (1994)). Some intuition for this result can be found recalling the argument put forward by Barro (2000), who argues that it might be that education has a positive contribution to growth only after minimum threshold has been achieved. While that threshold is not reached, increasing women's level of education can actually have a negative impact on growth because the resources used to educate women could have been used in productive activities. At a more general level, the fact that neither male nor female education are significant in the short-run shows the fundamental investment properties of human capital, i.e., a cost in the short-run that has a return only in the long-run.

I next turn to the results obtained for the medium-run. I run the same regressions as before but for periods of 10 years. The summary statistics and the Gini coefficients used are presented in Tables (8) and (12) in Appendix B. The results are reported in Table (3), which has the same structure as Table (2).

As can be seen, the results are very similar to the ones for the 5-year periods. In particular, there is an inverse-U relationship between (lagged) inequality and growth. Again, $\chi^2_{(10)} = 48.48$, which rejects the specification based on random effects at any level of significance. The Arellano and Bond-test for serial correlation is satisfied in every specification. Also, since I now have less periods, the problem of instrument proliferation seems less serious. For the regression with the full set of instrument, the Hansen test provides a value of 0.977 and the difference-in Sargan test provides a value of 1.00. Reducing to two the number of lags allowed to be used as instruments (Column (6)) helps solve this problem, but the difference-in Sargan test still provides a value of 0.909.

Compared to the short-run, reducing the number of lags now does help remove the problem of instrument proliferation. The signs for the coefficients of initial income, female and male education are for the most part consistent with the findings in Table (2). PPPI is not significant anymore. Interestingly, in the most restrictive specification all coefficients (with the exception of the one corresponding to male education) are significant.

In terms of the effect of inequality on growth, the 10-year period provides an inverse-U relationship as before, but the effect is sharper. The coefficients on the Gini coefficient and the Gini coefficient squared have the right signs and are significant (to different levels) in all specifications. Intuitively, this may happen because the 5-year periods do not completely offset the short-run variations related to the business cycle. The inverse-U effect of inequality thus remains over 10-year periods. However,

Table 3: **Regression results: Medium-run**

Estimation Method	FE (1)	RE (2)	AB (3)	RAB (4)	System GMM Full (5)	2 lags (6)	1 lag (7)	C (8)	C, 1 lag (9)
Income	-0.0393***	-0.0066**	-0.0356***	-0.0358***	0.0067	0.0081	0.0087	0.0239***	0.0355***
	(6.47)	(2.51)	(4.55)	(3.68)	(1.25)	(1.64)	(1.33)	(2.78)	(2.75)
Inequality	0.3348**	0.2846*	0.4684***	0.4594***	0.3320*	0.4096**	0.4024*	1.2998***	1.0924***
	(2.31)	(1.87)	(3.62)	(2.72)	(1.89)	(2.38)	(1.87)	(3.86)	(3.35)
Inequality^2	-0.3205*	-0.3799*	-0.4263***	-0.4188**	-0.4640**	-0.5472***	-0.5541**	-1.3400***	-1.1460***
	(1.83)	(2.09)	(2.83)	(2.04)	(2.09)	(2.62)	(2.15)	(3.65)	(3.37)
Female Education	0.0060	0.0042	0.0026	0.0016	-0.0011	0.0002	-0.0002	-0.0131	-0.0224**
	(1.01)	(1.00)	(0.30)	(0.18)	(0.18)	(0.03)	(0.04)	(1.39)	(2.25)
Male Education	0.0007	-0.0006	0.0055	0.0061	-0.0020	-0.0031	-0.0040	0.0114	0.0126
	(0.11)	(0.14)	(0.64)	(0.71)	(0.35)	(0.58)	(0.66)	(1.37)	(1.62)
PPPI	-0.0001	-0.0001	-0.00004	-0.00004	-0.0001	-0.0001	-0.0001	-0.0002*	-0.0003**
	(0.81)	(1.00)	(0.71)	(0.58)	(1.46)	(1.35)	(1.55)	(1.74)	(2.54)
Countries	90	90	90	90	90	90	90	90	90
Observations	327	327	241	241	327	327	327	327	327
Instruments			95	95	126	90	66	42	18
Arellano-Bond test (p-value)			0.284	0.243	0.467	0.468	0.449	0.370	0.322
Hansen test (p-value)				0.618	0.977	0.290	0.139	0.178	0.797
Diff-in Sargan test (p-value)					1.000	0.909	0.161	0.044	0.797

Note: Dependent variable is average annual per capita growth. Period dummies are not reported. t statistics are shown in parenthesis. Column (1) reports fixed-effect estimation, and column (2) reports random-effects estimation. Column (3) is the one-step Arellano and Bond estimator. Column (4) is the two-step Arellano and Bond estimator with the Windmeijer finite sample correction, columns (5)-(9) are the robust system-GMM estimator. Column (5) includes the full set of instruments. Column (6) allows instruments for up to 2-lags and column (7) allows for only 1 lag. Column (8) collapses the matrix of instruments. Column (9) provides the most restrictive specification: a collapsed matrix of instruments with only a 1-period lag. Significance: * significant at 10%; ** significant at 5%; *** significant at 1%.

this effect is economically less significant than over 5-year periods. For example, a country with a Gini coefficient one standard deviation of the mean that experiences a change in its Gini coefficient of one standard deviation will have an average change in growth of 0.14% per year. This is less than 50% of the impact found in the short-run. Figure 1 provides a clear picture of how the effect of inequality compares over these two different period lengths.

My preferred specification is now column (7) in Table (3), in which I limit the lags that can be used as instruments to 1.[23] I do not prefer column (8) as in the short-run because the level-instrument set does not satisfy the exogeneity restriction (the difference-in Sargan test provides a test-statistic of 0.044). Furthermore, recall that in principle we would like to use the estimates corresponding to the estimator with the full set of instruments. When there are too many instruments, the aim is to restrict their number without distorting the basic theoretical construction of the estimator.

In my preferred specification, the relationship between inequality and growth implies that the optimal Gini coefficient over 10-year periods is 36, which is significantly lower than in the short-run (49).[24] However, we should not read too much into this since the optimal Gini coefficient is higher with the collapsed matrix of instruments than with the reduced lags.[25] Despite this caveat, in all specifications I find that the short and medium-run relationship between inequality and growth follows an inverse-U shape.

As I mentioned above, Barro (2000) finds a different relationship for 10-year periods. To test for this I run an alternative specification in which *instead* of a quadratic term on inequality I include an interaction term between inequality and income level (not reported). While in this specification the signs on the inequality coefficient and on the interaction coefficient are consistent with the findings of Barro (2000), and they are significant in the specifications that use the system GMM estimator including reductions in the allowed lags that can be used as instruments, they are not significant in the specifications that collapse the matrix of instruments (as well as when using the Arellano and Bond estimator). More importantly, in all specifications the coefficients imply levels for the income threshold that are impossible to occur in practice (in the order of e^{1000}). Therefore, I do not adopt this specification and focus instead on the results obtained from the specification that includes the quadratic term.

The most important finding of the medium-run analysis is that the inverse-U relationship between inequality and growth found in the short-run is maintained. The next question is whether this relationship holds over 20-year periods, which I analyze next.

[23]Note, however, that the linear coefficient on inequality is significant only at the 10% level.

[24]A Gini coefficient of 36 corresponds to the inequality level of Portugal, which has the highest inequality among Western European countries. This level is also significantly below the average historical level of inequality in the United States (see Table (11)).

[25]Ideally, I should compare the same specifications over time. However, due to the different lengths of the panels, the appropriate specification does change when I analyze different period lengths.

4.2 Long-run: The Turning Point

So far I have showed that (lagged) inequality and growth are associated in a non-linear way over 5-year and 10-year periods. In particular, the relationship between inequality and growth has an inverse-U shape. Considering the available data, the obvious next question is to verify whether the same relationship holds over a longer period of time. Table (4) summarizes the results for the 20-year period. The summary statistics and the Gini coefficients used are presented in Appendix B, Tables (9) and (13).

As can be seen from the table, the inverse-U relationship found in the short and medium-run does not seem to hold for 20-year periods. Indeed, all coefficients become insignificant when I run the same regression as before. It thus seems that the relationship between the different regressors and growth changes when we move from 10 to 20-year periods. The fact that the data reflects this can shed some light on the apparent contradiction between the short-run and long-run results obtained in the literature over the last two decades. If both results are correct, there must exist some intermediate point at which the relationship changes. The evidence presented here shows that this point occurs between 10 and 20 years.

As a further exploration into these results, I follow Barro (2000) who also finds no relationship between inequality and growth in his basic regression. But, once he includes an interaction term between inequality and income, he does find that inequality retards growth in poor countries but it encourages it in rich ones. Table (5) reports the results for the 20-year periods once I include this interaction term (and eliminate the quadratic term).

Before discussing the findings, I first check the assumptions required for the specification. The Hausman test provides a test-statistic of 56.27, which rejects the assumption required for random effects estimation. Regarding the validity of instruments, columns (4)-(9) in Table (5) report Hansen and difference-in Sargan tests for the validity of instruments.[26] As can be seen, since the number of periods is small, instrument proliferation does not seem to pose a serious problem. Indeed, in this case the system-GMM estimator with the full set of instruments is identical to the one that restricts the lags to a maximum of 2. Thus, for this regression, my preferred specification is the one with the full set of instruments.

I find evidence consistent with Barro (2000) that inequality is bad for growth in poor countries but good for growth in rich ones. But, while Barro finds this association for 10-year periods, I find it for 20-year periods. The turning point occurs around 10,500 PPP international dollars (2005 as a base year). Also, the coefficient on income now is negative, and significant in the preferred specification, showing evidence of convergence over longer periods of time. The coefficient on female education is negative and insignificant, while the coefficient on male education is mostly positive, but also insignificant. The coefficient on the measure of market distortions, PPPI, while negative in all specifications, is not significant.

[26] Because the panel is shorter, it is not possible to calculate Arellano-Bond tests for AR(2).

Table 4: **Regression results: Long-run with non-linear effect**

Estimation Method	FE (1)	RE (2)	AB (3)	RAB (4)	System GMM Full (5)	2 lags (6)	1 lag (7)	C (8)	C, 1 lag (9)
Income	-0.0384***	-0.0075**	-0.0334***	-0.0347***	0.0018	0.0018	0.0028	0.0058	0.0075
	(7.59)	(2.51)	(3.41)	(7.20)	(0.48)	(0.48)	(0.49)	(1.46)	(1.55)
Inequality	0.0575	0.1091	-0.0932	-0.1010	0.1837	0.1837	0.1819	0.1469	0.1642
	(0.50)	(1.23)	(0.40)	(0.80)	(1.53)	(1.53)	(0.83)	(0.65)	(0.83)
Inequality^2	-0.0492	-0.1565	0.2084	0.1924	-0.2039	-0.2039	-0.2109	-0.1326	-0.1734
	(0.32)	(1.46)	(0.92)	(1.50)	(1.37)	(1.37)	(0.84)	(0.47)	(0.76)
Female	0.0039	-0.0081	0.0096	0.0104	-0.0071	-0.0071	-0.0085	-0.0059	-0.0058
Education	(0.54)	(1.55)	(0.83)	(1.18)	(0.85)	(0.85)	(1.02)	(0.88)	(0.78)
Male	-0.0025	0.0116	-0.0129	-0.0123	0.0097	0.0097	0.0094	0.0059	0.0036
Education	(0.35)	(2.23)	(0.88)	(1.11)	(1.09)	(1.09)	(1.04)	(0.78)	(0.41)
PPPI	-0.00001	-0.00002**	0.0001	0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001
	(0.21)	(2.23)	(1.13)	(0.87)	(1.43)	(1.43)	(1.29)	(1.52)	(1.28)
Countries	59	59	59	59	59	59	59	59	59
Observations	127	127	68	68	127	127	127	127	127
Instruments			20	20	33	33	27	21	15
Arellano-Bond test (p-value)									
Hansen test (p-value)					0.425	0.425	0.179	0.343	0.132
Diff-in Sargan test (p-value)					0.342	0.342	0.332	0.393	0.132

Note: Dependent variable is average annual per capita growth. Period dummies are not reported. t statistics are shown in parenthesis. Column (1) reports fixed-effect estimation, and column (2) reports random-effects estimation. Column (3) is the one-step Arellano and Bond estimator. Column (4) is the two-step Arellano and Bond estimator with the Windmeijer finite sample correction, columns (5)-(9) are the robust system-GMM estimator. Column (5) includes the full set of instruments. Column (6) allows instruments for up to 2-lags and column (7) allows for only 1 lag. Column (8) collapses the matrix of instruments. Column (9) provides the most restrictive specification: a collapsed matrix of instruments with only a 1-period lag. Significance: * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 5: **Regression results: Long-run with interaction effect**

Estimation							System GMM		
Method	FE	RE	AB	RAB	Full	2 lags	1 lag	C	C, 1 lag
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Income	-0.0420***	-0.0254***	-0.0298*	-0.0307***	-0.02611**	-0.0261**	-0.0270**	-0.0200	-0.0189
	(5.07)	(3.52)	(1.82)	(2.66)	(2.50)	(2.50)	(2.38)	(1.39)	(1.29)
Inequality	-0.0595	-0.3920***	0.1573	0.1080	-0.5671**	-0.5671**	-0.5864**	0.4937	-0.4640*
	(0.33)	(2.88)	(0.42)	(0.38)	(2.63)	(2.63)	(2.39)	(1.63)	(1.73)
Inequality*Income	0.0083	0.0423***	-0.0064	-0.0049	0.0612**	0.0612**	0.0643**	0.0577*	0.0521*
	(0.45)	(2.82)	(0.14)	(0.16)	(2.63)	(2.63)	(2.40)	(1.72)	(1.70)
Female	0.0039	-0.0081	0.0102	0.0141	-0.0072	-0.0072	-0.0071	-0.0072	-0.0051
Education	(0.54)	(1.64)	(0.94)	(1.41)	(0.94)	(0.94)	(1.21)	(1.18)	(0.76)
Male	-0.0023	0.0130***	-0.0104	-0.0135	0.0094	0.0094	0.0095	0.0080	0.0057
Education	(0.32)	(2.62)	(0.72)	(1.53)	(1.14)	(1.14)	(1.53)	(1.33)	(0.81)
PPPI	-0.0000	-0.00002	0.0001	0.00004	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001
	(0.17)	(0.50)	(1.07)	(0.37)	(1.18)	(1.18)	(0.94)	(1.34)	(1.17)
Countries	59	59	59	59	59	59	59	59	59
Observations	127	127	68	68	127	127	127	127	127
Instruments			20	20	33	33	27	21	15
Arellano-Bond									
test (p-value)									
Hansen test									
(p-value)				0.808	0.425	0.425	0.462	0.252	0.144
Diff-in Sargan									
test (p-value)					0.584	0.584	0.708	0.114	0.144

Note: Dependent variable is average annual per capita growth. Period dummies are not reported. t statistics are shown in parenthesis. Column (1) reports fixed-effect estimation, and column (2) reports random-effects estimation. Column (3) is the one-step Arellano and Bond estimator. Column (4) is the two-step Arellano and Bond estimator with the Windmeijer finite sample correction, columns (5)-(9) are the robust system-GMM estimator. Column (5) includes the full set of instruments. Column (6) allows instruments for up to 2-lags and column (7) allows for only 1 lag. Column (8) collapses the matrix of instruments. Column (9) provides the most restrictive specification: a collapsed matrix of instruments with only a 1-period lag. Significance: * significant at 10%; ** significant at 5%; *** significant at 1%.

The analysis so far shows that as the time-frame under analysis is increased, the relationship between inequality and growth tends to change. In the short-run and medium-run both lower and higher inequality have a negative impact on subsequent growth. But, in the medium-run a different pattern start to emerge: increased inequality tends to affect growth negatively in poor countries, but positively in rich countries.

More work is needed to explain why and how this change occurs. However, it can be concluded that there is a turning point between 10 and 20 years regarding the relationship between inequality and growth. What happens when we increase further the period length? I turn to this analysis in the next section.

4.3 Very Long-run: A Different Relationship

I analyze the very long-run effect of inequality on growth by running a cross-country regression, similar to the ones that originated the literature, but over a much longer period. The results are reported in Table (6) below.

Table 6: **Regression results: Very Long-run**

Estimation Method	OLS
	(1)
Income	-0.0098***
	(2.84)
Inequality	-0.0458**
	(2.32)
Female Education	-0.0156
	(1.56)
Male Education	0.0199*
	(1.92)
PPPI	-0.00004
	(0.86)
Countries	59
Observations	59

Note: Significance: * significant at 10%; ** significant at 5%; *** significant at 1%.

The very long-run relationship between inequality and growth seems to be linear and negative. However, the coefficient on inequality is not robust to including either a quadratic term or an interaction term on inequality. This shows the difficulties inherent in trying to find a clear-cut relationship between inequality and growth over such a long period of time. Hence, this result should be taken with care. Furthermore, recall that strictly speaking this result is not comparable with the previous ones since the estimation strategy is different. Despite these caveats, it is important to remember that this result is consistent with those obtained by Easterly (2007) using instrumental variables. His argument is that we should look at the very long-run relationship between inequality and growth and, in this context, he finds that inequality is detrimental to growth. The argument presented in this paper complements this finding in that it shows that the dynamic process of the relationship between inequality and growth is relevant as well.

Regarding the other variables, the coefficient on initial income is negative and significant, showing evidence of convergence in the very long-run. Female education still has a negative effect on growth, but it is not significant. Male education, on the other hand, still has a positive sign as in the previous sections, but now it becomes significant, confirming the importance of human capital for long-run growth. Finally, as in the 20-year period analysis, market distortions do not seem to have an effect on growth. These conclusions are robust to the inclusion of a quadratic and/or an interaction term on inequality.[27]

4.4 Summary of Results

In the previous sections, I have argued that the relationship between inequality and growth changes as we look at different period lengths. The relationship is non-linear in the short, medium and long-run, but it seems linear in the very long-run. Figure 1 summarizes the main argument: the nature of the relationship between inequality and growth changes over time.[28] When I look at 5-year periods, the relationship has an inverse-U shape. The same relationship holds over 10-year periods, but it is shifted downwards, implying that the effect of inequality on growth turns from positive to negative at a lower level of inequality compared to the short-run. In the long-run, the relationship between inequality and growth depends on the level of income. In particular, inequality has a positive effect on growth in (very) rich countries, and a negative effect on growth in poor countries. To show this effect, I introduce a lower x-axis, which measures income per capita. In Figure 1, the graph for this period length is constructed assuming there is a negative linear relationship between inequality and the level of income. This relationship *roughly* approximates the observed one in the panel of countries analyzed; I make this assumption to have a smooth graph comparable to the others. As can be seen, the graph for the long-run also depicts a similar relationship as those of the short-run and medium-run, but recall that now it depends on the level of income. Finally, the graph of the very long-run relationship is a straight line with a negative slope.

[27] See Table (**??**) below.

[28] To clarify, the lower x-axis is relevant only for depicting the long-run between inequality and growth, when it depends on the level of income. For the short, medium, and very long-run, the relationship can be read recurring only to the upper x-axis. Also, for comparability, in Figure 1 I assume that the constant term in all specifications is equal to 0.

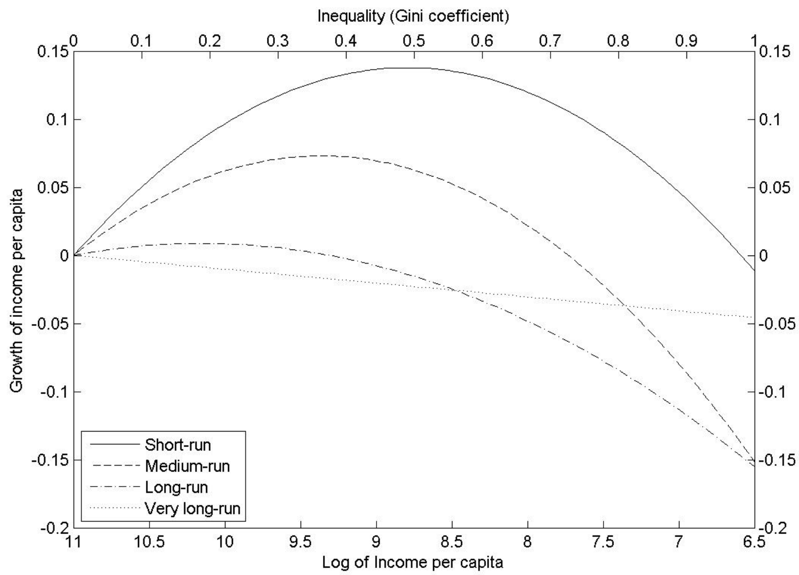

Figure 1: Inequality and growth

5 Conclusion

In this paper I have analyzed the short, medium, long and very long-run relationship between inequality and growth. I benefit from a large dataset that in the broadest specification covers 100 countries over a period of almost 60 years. It incorporates recent updates to the Penn World Table, the UNU-WIDER inequality dataset and the Barro and Lee education dataset.

Using a system-GMM estimator with a restricted number of instruments I find an inverse-U association between inequality and growth in the short-run (5-year periods). This relationship remains in the medium-run (10-year periods), but it is economically weaker. Finally, it disappears over longer time spans (20-year periods). While the 5 and 10-year findings are consistent with the criticism put forward by Banerjee and Duflo (2003) that inequality and growth are not linearly related, I show that this nonlinearity is found using a system-GMM estimator with restricted instruments that solves the weak instrument problem of the Arellano and Bond estimator as well as the problem of instrument proliferation.

Perhaps the most interesting finding is the fact that this relationship does not remain in the long-run (20-year periods). This implies the existence of some structural change when moving from 10 to 20-year periods. Over 20 years I find that the coefficient on inequality becomes negative in all specifications using the system-GMM estimator, and it is significant in the preferred one. However, this result holds only when I also include an interaction term between inequality and income per capita. Thus, over the 20-year period, inequality seems to have a negative effect on growth in poor countries, but a positive effect on growth in rich ones. This finding is consistent with Barro (2000), who obtains a similar result, but over 10-year periods.

Finally, when I run a very long-run cross-country regression of the effect of inequality on growth I find a linear, negative relationship. This is consistent with the original works on the long-run relationship between inequality and growth (Alesina and Rodrik, 1994; Persson and Tabellini, 1994). However, these studies consider the long-run to be around 20 years, while I consider it to be almost 40 years, and hence the results are not quite comparable. My findings for the 20-year periods, on the other hand, clearly contradict previous evidence as I find that the effect of inequality on growth over this time frame depends on the level of income, being negative for poor countries and positive for rich ones.

Much more work remains to be done regarding the specific mechanisms through which the relationship between inequality and growth tends to change over different time periods. The recent argument put forward by Halter et al. (2010) provides a starting point to understand them: the economic benefits of inequality take place mostly in the short-run, while the social and political costs take place mostly in the long-run. However, this leaves aside the apparent non-linearity between inequality and growth observed over different time frames. A complementary explanation is based on the salience of inequality. In the short and medium-run, high levels of inequality encourage social conflict and the search for transfers, both of which are costly to economic growth. At the same time, however, too much equality also affect growth as the incentives to invest and progress are distorted. The combination of these effects leads to the observed inverse-U relationship. In the long-run, the dynamics are richer. Even relatively low levels of inequality become salient when it persists for longer periods of time. Thus, lower inequality levels (compared to those necessary in the short and medium-run) can lead to social conflict, which in turn reduces growth. This effect is likely to be seen at an earlier stage in poor countries, since the poor in those countries face much more restrictive life-conditions that make them act at an earlier point in time that their counterparts in richer countries. In the very long-run, this effect also appears in rich countries.

The effect of other variables on growth is also worth analyzing. First, I find evidence of divergence in the short and medium-run. Over a 20-year period, I find some evidence of convergence. In the long-run, the coefficient remains negative and significant. Thus, it seems that the effect of initial income may also vary depending on the time-frame analyzed. The most puzzling result concerns human capital. The effect of female education does not seem to contribute to growth at any time frame. The coefficient is consistently negative, and significant in some specifications in the short and medium-run. However, it is never significant in the long and very long-run. Male education on the other hand has a positive coefficient attached to it in most specifications, but it only becomes significant in the very long-run. Thus, human capital seems to play a key role only over this time-frame. Finally, the effect of market distortions on growth is consistently negative for all specifications, but it is only significant in the short-run and marginally so in the medium-run, thus showing that over time societies may learn ways around costly blocks to investment.

In the end, the main message of this paper is that the observed relationships between variables depends on the time span considered. This is certainly not a new idea in economics but the existence of new databases allows us to take this point much more seriously and to analyze old questions under a fresh perspective.

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Appendix

Here I present tables of the summary statistics of the data used for each regression as well as detailed tables of the Gini coefficients. Tables (7), (8), (9) and (10) show the summary statistics for 5, 10, 20 and 37-year periods, respectively, while Tables (11), (12), (13) and (14) show the corresponding Gini coefficients.[29]

[29]Recall that the Gini coefficients used in all regressions are re-scaled to the interval $0 - 1$.

Table 7: **Summary Statistics Short-run**

Variable	Definition	Year	N	Mean	Standard deviation	Minimum	Maximum
Income	Ln of Real GDP per capita, base year 2005	1950	47	8.26	0.80	6.69	9.61
		1955	63	8.18	0.86	6.35	9.63
		1960	79	8.08	0.96	6.18	9.80
		1965	80	8.23	0.99	6.23	9.94
		1970	89	8.35	1.00	6.41	10.11
		1975	89	8.48	1.02	6.43	10.12
		1980	89	8.59	1.05	6.50	10.24
		1985	89	8.63	1.05	6.43	10.34
		1990	95	8.74	1.09	6.36	10.68
		1995	102	8.78	1.07	6.45	10.82
		2000	102	8.90	1.10	6.52	11.06
		2005	102	9.03	1.10	6.48	11.17
Inequality	Inequality, measured by the Gini coefficient	1950	10	0.43	0.11	0.30	0.70
		1955	21	0.44	0.11	0.23	0.67
		1960	36	0.45	0.11	0.20	0.68
		1965	45	0.43	0.10	0.21	0.68
		1970	55	0.43	0.12	0.22	0.68
		1975	55	0.39	0.10	0.17	0.61
		1980	57	0.39	0.11	0.20	0.65
		1985	58	0.37	0.11	0.20	0.60
		1990	81	0.38	0.12	0.20	0.63
		1995	97	0.42	0.12	0.20	0.75
		2000	92	0.42	0.11	0.21	0.67
Female Education	Average years of secondary schooling in the female population aged over 25	1950	102	0.44	0.59	0.00	2.83
		1955	102	0.50	0.64	0.00	3.03
		1960	102	0.58	0.71	0.00	3.19
		1965	102	0.69	0.78	0.00	3.77
		1970	102	0.83	0.88	0.00	4.30
		1975	102	1.03	1.02	0.00	4.76
		1980	102	1.26	1.14	0.00	5.11
		1985	102	1.51	1.21	0.01	5.10
		1990	102	1.77	1.28	0.02	5.12
		1995	102	2.06	1.37	0.04	5.16
		2000	102	2.29	1.45	0.09	5.43
Male Education	Average years of secondary schooling in the male population aged over 25	1950	102	0.66	0.67	0.00	3.19
		1955	102	0.75	0.73	0.00	3.41
		1960	102	0.83	0.81	0.00	3.59
		1965	102	1.01	0.89	0.00	4.02
		1970	102	1.20	1.02	0.00	4.24
		1975	102	1.44	1.13	0.00	4.77
		1980	102	1.70	1.24	0.00	5.09
		1985	102	1.96	1.28	0.04	5.22
		1990	102	2.20	1.32	0.09	5.32
		1995	102	2.48	1.39	0.26	5.93
		2000	102	2.70	1.46	0.30	6.98
PPPI	Price level of investment, measured as the PPP of investment/exchange rate relative to the United States	1950	48	71.57	49.99	12.38	265.04
		1955	64	80.48	114.97	12.85	921.86
		1960	80	66.12	45.30	13.30	261.47
		1965	81	69.86	47.24	16.15	329.88

Table 7: (continued)

Variable	Definition	Year	N	Mean	Standard deviation	Minimum	Maximum
		1970	89	63.67	40.23	14.60	254.58
		1975	89	79.15	48.45	12.89	329.44
		1980	89	102.05	177.04	15.75	1707.95
		1985	89	59.90	29.73	19.29	187.71
		1990	95	77.16	59.09	0.29	472.55
		1995	102	68.58	43.12	19.45	360.25
		2000	102	60.24	37.70	17.62	315.65

Sources: Income and PPPI: Heston et al. (2009). Female and Male education: Barro and Lee (2010). Inequality: UNU-WIDER (2008b).

Table 8: **Summary Statistics: Medium-run**

Variable	**Definition**	**Year**	**N**	**Mean**	**Standard deviation**	**Minimum**	**Maximum**
Income	Ln of Real GDP per capita, base year 2005	1950	46	8.30	0.77	6.69	9.61
		1960	80	8.11	0.92	6.18	9.80
		1970	86	8.44	0.95	6.41	10.11
		1980	86	8.72	0.96	6.50	10.24
		1990	92	8.88	0.98	6.36	10.68
		2000	92	9.05	1.04	6.52	11.06
		2007	92	9.24	1.05	6.83	11.26
Inequality	Inequality, measured by the Gini coefficient	1950	9	0.43	0.12	0.30	0.70
		1960	41	0.45	0.10	0.20	0.68
		1970	60	0.43	0.11	0.21	0.68
		1980	67	0.40	0.10	0.20	0.65
		1990	84	0.40	0.12	0.20	0.63
		2000	84	0.42	0.12	0.21	0.75
Female	Average years of secondary schooling in the female population aged over 25	1950	92	0.41	0.56	0.00	2.66
		1960	92	0.53	0.67	0.00	3.18
		1970	92	0.76	0.82	0.01	4.30
		1980	92	1.16	1.05	0.02	5.11
		1990	92	1.68	1.14	0.06	5.12
		2000	92	2.23	1.31	0.09	5.43
Male	Average years of secondary schooling in the male population aged over 25	1950	92	0.61	0.63	0.01	2.88
		1960	92	0.76	0.76	0.02	3.35
		1970	92	1.11	0.95	0.05	4.24
		1980	92	1.58	1.14	0.11	5.09
		1990	92	2.11	1.20	0.23	5.32
		2000	92	2.64	1.33	0.31	6.98
PPPI	Price level of investment, measured as the PPP of investment/exchange rate relative to the United States	1950	46	69.39	48.30	12.38	265.04
		1960	80	64.45	42.43	13.30	261.47
		1970	86	65.36	40.78	22.65	254.58
		1980	86	89.43	54.73	29.86	387.79
		1990	92	75.54	46.67	0.29	290.17
		2000	92	62.30	38.32	19.08	315.65

Sources: Income and PPPI: Heston et al. (2009). Female and Male education: Barro and Lee (2010). Inequality: UNU-WIDER (2008b).

Table 9: **Summary Statistics: Long-run**

Variable	**Definition**	**Year**	**N**	**Mean**	**Standard deviation**	**Minimum**	**Maximum**
Income	Ln of Real GDP per capita, base year 2005	1950	34	8.19	0.79	6.69	9.47
		1970	55	8.59	0.93	6.41	9.89
		1990	55	9.05	0.95	6.36	10.34
		2007	55	9.44	0.98	6.83	10.79
Inequality	Inequality, measured by the Gini coefficient	1950	9	0.43	0.12	0.30	0.70
		1970	55	0.42	0.11	0.20	0.68
		1990	55	0.41	0.12	0.21	0.63
Female	Average years of secondary schooling in the female population aged over 25	1950	55	0.44	0.59	0.00	2.66
		1970	55	0.82	0.85	0.01	4.30
		1990	55	1.82	1.21	0.12	5.12
Male	Average years of secondary schooling in the male population aged over 25	1950	55	0.66	0.62	0.01	2.88
		1970	55	1.17	0.98	0.06	4.24
		1990	55	2.23	1.26	0.33	5.32
PPPI	Price level of investment, measured as the PPP of investment/exchange rate relative to the United States	1950	34	63.43	26.39	12.38	126.09
		1970	55	67.93	43.20	23.03	254.58
		1990	55	85.76	52.71	23.10	290.17

Sources: Income and PPPI: Heston et al. (2009). Female and Male education: Barro and Lee (2010). Inequality: UNU-WIDER (2008b).

Table 10: **Summary Statistics: Very Long-run**

Variable	**Definition**	**Year**	**N**	**Mean**	**Standard deviation**	**Minimum**	**Maximum**
Income	Ln of Real GDP per capita, base year 2005	1970	76	8.44	0.93	6.41	9.89
		2007	76	9.38	1.26	6.58	11.43
Inequality	Inequality, measured by the Gini coefficient	1970	76	0.44	0.11	0.20	0.68
Female	Average years of secondary schooling in the female population aged over 25	1970	76	0.73	0.84	0.01	4.30
Male	Average years of secondary schooling in the male population aged over 25	1970	76	1.03	0.95	0.04	4.24
PPPI	Price level of investment, measured as the PPP of investment/exchange rate relative to the United States	1970	76	66.45	44.32	13.79	254.58

Sources: Income and PPPI: Heston et al. (2009). Female and Male education: Barro and Lee (2010). Inequality: UNU-WIDER (2008b).

Table 11: **Gini Coefficients Short-run**

Country	1945-50	1951-55	1956-60	1961-65	1966-70	1971-75	1976-80	1981-85	1986-90	1991-95	1996-2000	Mean
Algeria									39.9	35.4		37.7
Argentina								39.8	44.4			41.8
Armenia									26.9	36.6	38.4	34.0
Australia	30.3	27.2	30.9	30.3	31.0	26.6	27.8	32.5	33.8	34.2	31.0	30.5
Austria					29.5	26.7	24.3	28.3	22.7	27.0	23.7	26.0
Bangladesh			41.8	33.8	42.4	36.9	35.1	39.0	33.6	37.0	41.2	37.9
Belgium							28.2	22.5	23.4	29.8	26.8	27.1
Bolivia									54.5	52.7	61.7	56.3
Botswana									47.7	53.7		50.7
Brazil					59.0	62.5	59.6	58.9	63.1	57.0	59.0	59.5
Bulgaria			24.5	21.1	21.2	17.5	23.4	27.9	21.2	36.8	30.8	24.9
Burundi										33.3	41.8	37.6
Cambodia										46.0	44.5	45.3
Canada		32.5	32.1	31.5	36.1	33.1	28.5	28.8	28.1	28.8	30.1	31.0
Chile				46.2	44.0	47.1			57.4	54.5	59.5	51.5
China								24.3	23.0	31.1		27.8
Colombia				48.2	49.6	47.5	44.6		48.5	57.9	56.3	50.4
Costa Rica						46.4	43.0	47.6	45.3	45.8	50.1	46.9
Cote d'Ivoire								50.6	45.9	43.9	44.0	46.1
Cuba						28.3	27.0					36.9
Czech Republic									20.4	26.0	26.1	24.2
Denmark	39.0	40.0		37.0	24.9	22.5	31.6	20.1	23.7	20.0	21.0	28.0
Dominican Republic							45.0	43.4	47.0	51.6	52.0	48.0
Ecuador									43.7	55.6	58.8	55.3
Egypt			37.0	35.0						28.7	37.8	35.3
El Salvador										50.6	51.9	49.1
Estonia									24.0	35.3	36.4	31.9
Finland					30.8	28.3	22.7	22.4	21.5	22.9	26.8	25.1
France					34.0	32.0	32.8	31.4	32.7	30.2	29.3	31.8
Gambia										59.4	47.1	53.3
Germany	39.6	38.4	38.0	38.0	39.2	37.3	36.6	30.0	29.7	29.4	24.6	34.6
Ghana									36.0	33.9	40.7	36.9
Greece			41.1	44.1	46.3	41.3		39.8	37.0	35.1	32.3	39.6
Guyana										54.0	44.2	49.1
Honduras									57.6	55.9	55.9	57.9
Hong Kong			47.9	50.1	49.0	43.8	43.0	44.6	42.2	43.4	51.4	46.2
Hungary		23.3	20.4			22.6	20.7	21.3	26.8	22.6	23.7	22.7
India		33.8	32.5	34.5	30.2	28.9	30.9	30.1	27.7	28.4	36.0	31.3
Indonesia				38.9	34.6	43.9	38.0	33.0	34.0	34.0	30.8	35.9
Iran					41.9	46.0						43.7
Ireland						37.4	36.6		36.0	34.3	30.1	34.9
Israel									34.7	35.5	38.0	36.1
Italy					39.0	39.2	37.5	32.0	29.8	33.9	29.8	35.4
Jamaica					62.8	45.7	65.5		41.7	39.7	38.5	50.2
Japan		31.0	36.0	34.8	41.4	36.9	33.4	29.1	31.2	31.6	31.9	33.7
Jordan						42.1	36.5		36.0	40.0	36.3	38.2
Kazakhstan								25.7	28.9	32.7	35.4	30.7
Kenya	70.0	63.0	68.0	63.0	68.0					44.3	55.6	61.2
Korea				28.9	31.2	40.2	36.7	37.0	32.0	32.4	37.1	34.4
Kyrgyzstan								24.3	30.8	39.5	47.0	35.4
Laos										29.9	36.5	33.2
Latvia									24.0	30.9	32.1	29.0
Lesotho									63.0	69.0	60.0	64.0
Lithuania									24.8	37.2	34.7	32.2
Luxembourg								26.4	16.6	28.9	30.2	25.5

Table 11: (continued)

Country	1945-50	1951-55	1956-60	1961-65	1966-70	1971-75	1976-80	1981-85	1986-90	1991-95	1996-2000	Mean
Malawi							53.1	59.9		62.0	49.3	56.1
Malaysia							50.6	51.5	49.1	50.0	44.3	48.2
Mali									36.5	54.0		45.3
Mauritania									42.4	38.9	39.0	40.1
Mauritius						41.9	45.7		39.8	37.9	38.7	40.8
Mexico	52.3		53.0	54.2	53.6	61.2	50.0	50.6	53.1	50.2	53.2	53.1
Moldova									26.7	41.1	39.2	35.7
Morocco					56.0	59.0	54.0	38.9		39.2	39.4	48.1
Netherlands	41.0	44.4		43.7	36.2	29.8	28.1	28.1	32.1	25.2	32.0	34.1
New Zealand						30.0	34.7	35.3	29.0	33.1	33.8	32.6
Nicaragua										56.5	54.1	55.3
Norway					30.5	35.0	31.3	31.8	25.2	25.7	28.8	29.8
Pakistan				35.6	32.9	34.0	36.7	35.0	40.7	41.0	29.6	35.7
Panama									52.0	54.7	56.8	53.9
Paraguay										58.4	55.5	56.9
Peru				60.2	41.3	55.0		57.0	42.7	44.8	49.6	50.1
Philippines			45.2	46.5				44.7	45.7	46.2	49.4	46.1
Poland						24.0	23.1	23.3	28.3	32.2	34.2	27.5
Portugal						40.1	36.8		32.9	37.4	36.8	36.8
Romania									22.9	31.1	30.3	28.1
Russia								25.1	26.9	44.6	48.3	36.2
Singapore					49.8	40.0	39.5	47.0	46.0	47.0	46.7	45.1
Slovak Republic									20.0	20.0	26.0	24.2
Slovenia									23.2	25.1	24.8	24.4
South Africa				55.0	51.0	47.0	49.0	47.0	63.0	59.0	56.5	53.4
Spain						35.6	34.2	24.9	31.7	33.2	31.5	32.8
Sri Lanka				46.7	35.3	39.8	27.6	44.9	46.0	44.7	61.0	43.7
Sweden					29.5	21.4	20.4	20.5	24.6	25.6	26.7	24.1
Switzerland							34.5	32.3		35.9	31.8	33.6
Taiwan		56.1	43.9	32.8	29.9	29.3	27.7	29.0	30.9	31.5	31.2	34.2
Tanzania							52.0	52.0				46.3
Thailand				43.7	43.8	41.2	45.1	48.3	47.4	43.3	44.8	44.7
Trinidad &Tobago						45.4	46.1		42.6	49.3		45.9
Tunisia						44.0	43.0	43.0	41.0			42.3
Turkey						51.5	51.0	45.0	46.5	46.7	39.8	48.0
Uganda										35.2	46.9	41.1
Ukraine									22.8	36.4	42.7	31.6
United Kingdom	34.0	34.0	35.4	24.4	25.4	23.7	25.2	27.7	33.5	32.8	34.6	30.1
United States	43.1	42.0	42.3	41.7	39.3	39.1	39.7	41.6	42.7	44.8	45.7	42.0
Uruguay								39.6	42.4	42.3	44.3	42.1
Venezuela						47.3	47.5	44.9	42.5	46.3	45.8	45.6
Vietnam										34.4	37.3	35.9
Yemen										39.3	21.8	30.5
Zambia						57.0	55.6			64.7	66.6	61.0
Zimbabwe									56.6	73.1		64.8
Mean	43.51	41.88	43.27	42.98	43.11	38.98	39.02	37.29	37.68	41.71	41.99	40.61

Note: Gini coefficient is taken from latest available data within the given period.

Table 12: **Gini Coefficients Medium-Run**

Country	1941-50	1951-60	1961-70	1971-80	1981-90	1991-2000	Mean
Algeria					39.9	35.4	37.7
Australia	30.3	30.9	31.0	27.8	33.8	31.0	30.8
Austria			29.5	24.3	22.7	23.7	25.1
Bangladesh		41.8	33.8	36.9	33.6	41.2	37.5
Belgium			32.1	28.2	23.4	26.8	27.6
Bolivia					54.5	61.7	58.1
Botswana					47.7	53.7	50.7
Brazil		57.2	59.0	59.6	63.1	59.0	59.6
Bulgaria		24.5	21.1	23.4	21.2	30.8	24.2
Cameroon					49.0	50.8	49.9
Canada		32.1	36.1	28.5	28.1	30.1	31.0
Chile			44.0	47.1	57.4	59.5	52.0
China Version 2					23.0	31.1	27.0
Colombia			49.6	44.6	48.5	56.3	49.7
Costa Rica			50.0	43.0	45.3	45.8	46.0
Cote d'Ivoire					45.9	44.0	45.0
Croatia					22.2	30.4	26.3
Cuba		56.7	35.4	27.0			39.7
Czech Republic					20.4	26.1	23.3
Denmark	39.0	40.0	24.9	31.6	23.7	21.0	30.0
Dominican Republic			49.1	45.0	47.0	52.0	48.3
Ecuador					43.7	58.8	51.3
Egypt		37.0	35.0	38.0			36.7
Estonia					24.0	36.4	30.2
Finland		41.0	30.8	22.7	21.5	26.8	28.6
France		47.6	34.0	32.8	32.7	29.3	35.3
Germany	39.6	38.0	39.2	36.6	29.7	24.6	34.6
Ghana					36.0	33.9	35.0
Greece		41.1	46.3	41.3	37.0	32.3	39.6
Guatemala				54.2	53.7	54.5	54.1
Haiti					51.5	50.9	51.2
Honduras					57.6	55.9	56.8
Hong Kong		47.9	49.0	43.0	42.2	51.4	46.7
Hungary				20.7	26.8	23.7	22.9
India		32.5	30.2	30.9	27.7	36.0	31.5
Indonesia			34.6	38.0	34.0	30.8	34.3
Iran			41.9	46.0	42.9	44.0	43.7
Ireland				36.6	36.0	30.1	34.2
Israel				36.3	34.7	38.0	36.3
Italy			39.0	37.5	29.8	29.8	35.6
Jamaica		57.7	62.8	65.5	41.7	38.5	53.2
Japan		36.0	41.4	33.4	31.2	31.9	34.8
Jordan				36.5	36.0	36.3	36.3
Kenya	70.0	68.0	68.0		57.3	55.6	63.8
Korea		34.0	31.2	36.7	32.0	37.1	34.2
Lesotho					63.0	69.0	66.0
Luxembourg					26.4	30.2	28.3
Malawi				53.1	59.9	49.3	54.1
Malaysia		42.0	50.0	50.6	49.1	50.0	48.3
Mali					36.5	54.0	45.3
Mauritania					42.4	38.3	40.4
Mauritius				45.7	39.8	38.7	41.4
Mexico	52.3	53.0	53.6	50.0	53.1	53.2	52.5
Morocco		50.0	56.0	54.0	38.9	39.2	47.6
Netherlands	41.0	44.4	36.2	28.1	32.1	32.0	35.6

Table 12: (continued)

Country	1941-50	1951-60	1961-70	1971-80	1981-90	1991-2000	Mean
New Zealand				34.7	29.0	33.8	32.5
Norway		38.8	30.5	31.3	25.2	28.8	30.9
Pakistan			32.9	36.7	40.7	32.5	35.7
Panama			58.7	47.6	52.0	56.8	53.8
Peru			41.3	55.0	42.7	49.6	47.2
Philippines		45.2	46.5	45.2	45.7	49.4	46.4
Poland				23.1	28.3	34.2	28.5
Portugal				36.8	33.5	36.8	35.7
Romania					22.9	30.3	26.6
Russia					26.9	48.3	37.6
Singapore			49.8	39.5	47.0	46.7	45.8
Slovak Republic					20.0	26.0	23.0
Slovenia					23.0	24.8	23.9
South Africa			51.0	49.0	63.0	59.0	55.5
Spain			38.8	34.2	31.7	31.5	34.1
Sri Lanka		47.3	35.3	27.6	46.0	61.0	43.4
Sweden			29.5	20.4	24.6	26.7	25.3
Switzerland				34.5	32.3	31.8	32.9
Taiwan		43.9	29.9	27.7	30.9	31.2	32.7
Tanzania			43.3	52.0	52.0	38.0	46.3
Thailand			43.8	41.2	47.4	44.8	44.3
Trinidad &Tobago				46.1	42.6	49.3	46.0
Tunisia			42.3	43.0	41.0	40.6	41.7
Turkey		53.0	50.5	51.5	46.5	46.7	49.6
United Kingdom	34.0	35.4	25.4	25.2	33.5	34.6	31.4
United States	43.1	42.3	39.3	39.7	42.7	45.7	42.1
Uruguay					42.4	44.3	43.4
Venezuela			44.8	47.5	42.5	45.8	45.2
Zimbabwe					56.6	73.1	64.8
Mean	43.44	44.72	42.09	39.79	38.58	40.89	40.85

Note: Gini coefficient is taken from latest available data within the given period.

Table 13: **Gini Coefficients Long-run**

Country	1931-50	1951-70	1971-90	Mean
Australia	30.3	31.0	33.8	31.7
Austria		29.5	24.3	26.9
Bangladesh		33.8	33.6	33.7
Belgium		32.1	23.4	27.7
Brazil		59.0	63.1	61.0
Bulgaria		21.1	21.2	21.1
Canada		36.1	28.1	32.1
Chile		44.0	57.4	50.7
Colombia		49.6	48.5	49.0
Costa Rica		50.0	45.3	47.6
Cuba		35.4	27.0	31.2
Denmark	39.0	24.9	23.7	29.2
Dominican Republic		49.1	47.0	48.0
Egypt		35.0	38.0	36.5
Finland		30.8	21.5	26.1
France		34.0	32.7	33.4
Germany	39.6	39.2	29.7	36.2
Greece		46.3	37.0	41.6
Honduras		62.0	57.6	59.8
Hong Kong		49.0	42.2	45.6
Hungary		20.4	26.8	23.6
India		30.2	27.7	29.0
Indonesia		34.6	34.0	34.3
Iran		41.9	42.9	42.4
Italy	41.7	39.0	29.8	36.8
Jamaica		62.8	41.7	52.3
Japan		41.4	31.2	36.3
Kenya	70.0	68.0	57.3	65.1
Korea		31.2	32.0	31.6
Malaysia		50.0	49.1	49.5
Mexico	52.3	53.6	53.1	53.0
Morocco		56.0	54.0	55.0
Netherlands	41.0	36.2	32.1	36.4
Norway		30.5	25.2	27.9
Pakistan		32.9	40.7	36.8
Panama		58.7	52.0	55.4
Peru		41.3	42.7	42.0
Philippines		46.5	45.7	46.1
Sierra Leone		44.5	63.7	54.1
Singapore		49.8	47.0	48.4
South Africa		51.0	63.0	57.0
Spain		38.8	31.7	35.3
Sri Lanka		47.3	46.0	46.6
Sweden	41.0	29.5	24.6	31.7
Taiwan		29.9	30.9	30.4
Tanzania		43.3	52.0	47.6
Thailand		43.8	47.4	45.6
Trinidad &Tobago		46.0	46.1	46.1
Tunisia		42.3	41.0	41.6
Turkey		50.5	46.5	48.5
United Kingdom	34.0	25.4	33.5	31.0
United States	43.1	39.3	42.7	41.7
Venezuela		44.8	42.5	43.7
Mean	43.20	42.25	41.14	41.81

Table 13: (continued)

Country	1931-50	1951-70	1971-90	Mean

Note: Gini coefficient is taken from latest available data within the given period.

Table 14: **Gini Coefficients Very Long-run**

Country	1950-70	Mean
Australia	31.0	31.0
Austria	29.5	29.5
Bangladesh	33.8	33.8
Barbados	41.8	41.8
Belgium	32.1	32.1
Brazil	59.0	59.0
Bulgaria	21.1	21.1
Canada	36.1	36.1
Chile	44.0	44.0
China	32.8	32.8
Colombia	49.6	49.6
Costa Rica	50.0	50.0
Cuba	35.4	35.4
Denmark	24.9	24.9
Dominican Republic	49.1	49.1
Ecuador	63.0	63.0
Egypt	35.0	35.0
El Salvador	46.2	46.2
Finland	30.8	30.8
France	34.0	34.0
Germany	39.2	39.2
Greece	46.3	46.3
Honduras	62.0	62.0
Hong Kong	49.0	49.0
Hungary	20.4	20.4
India	30.2	30.2
Indonesia	32.7	32.7
Iran	41.9	41.9
Italy	39.0	39.0
Jamaica	62.8	62.8
Japan	41.4	41.4
Kenya	68.0	68.0
Korea	31.2	31.2
Malaysia	50.0	50.0
Mexico	53.6	53.6
Morocco	56.0	56.0
Netherlands	36.2	36.2
New Zealand	68.6	68.6
Norway	30.5	30.5
Pakistan	32.9	32.9
Panama	58.7	58.7
Peru	41.3	41.3
Philippines	46.5	46.5
Sierra Leone	44.5	44.5
Singapore	49.8	49.8
South Africa	51.0	51.0
Spain	38.8	38.8
Sri Lanka	47.3	47.3
Sudan	45.2	45.2
Sweden	29.5	29.5
Taiwan	29.9	29.9
Tanzania	43.3	43.3
Thailand	43.8	43.8
Trinidad &Tobago	46.0	46.0
Tunisia	42.3	42.3

Table 14: (continued)

Country	1950-70	Mean
Turkey	50.5	50.5
United Kingdom	25.4	25.4
United States	39.3	39.3
Venezuela	44.8	44.8
Mean	43.25	43.25

Note: Gini coefficient is taken from latest available data within the given period.